Inside out and outside in:

The coevolution of organizations' knowledge base and network position

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Abstract

This paper argues that an organization's knowledge base and network position dynamically co-evolve. Specifically, we hypothesize that moving towards the core (periphery) of an R&D alliance network induces organizations to develop a generalist (specialized) knowledge base; at the same time, developing a generalist (specialized) knowledge base induces organizations to move towards the core (periphery) of the R&D network. To test this self-reinforcing causal cycle, we analyze a large panel data set describing all R&D collaboration alliances in the US between 1985 and 2003. The data strongly support our argument and hypotheses. In addition to illuminating the dynamic relationship linking organizations to their external environment, the paper unveils a deep-rooted theoretical link between network and knowledge-based views of the firm.

Keywords: Co-evolution, Knowledge Base, R&D Alliance Networks, Specialization, Generality, Core-periphery.

Introduction

The complex relationship linking organizations to their external environment has been a chief topic of investigation among organizational scholars for over half a century (Volberda et al. 2012). While early works were primarily concerned with the role of environmental uncertainty (Lawrence and Lorsch 1967), later research considered a wide range of dimensions including environmental dynamism (Davis et al. 2009), turbulence (Siggelkow and Rivkin 2005), complexity (Van de Ven et al. 2012), consensus (Cattani et al. 2008), and density (Lomi et al. 2010). Complementing this line of inquiry, an important stream of research has investigated how organizations strategically position themselves where environmental conditions are most favorable (Song et al. 2002).

Across these research streams, the external environment is usually assumed to exogenously affect the organization's internal resource base (Baum and Singh 1994). This assumption is problematic, though, because "environments affect organizations through the process of making available or withholding resources" that for the most part are held by other organizations (Aldrich 1976, p. 61, Podolny and Page 1998). Contrary to macro environmental characteristics such as density or dynamism, inter-organizational networks do not exogenously affect organizations' internal resource base (Stuart and Sorenson 2007). Insofar as organizations form and dissolve inter-organizational ties in an attempt to draw resources from the external environment (Ahuja 2000a), a more plausible and theoretically insightful hypothesis is that the resource base that develops within the boundaries of individual organizations systematically coevolves with the broader network that binds those organizations together (Ahuja et al. 2012, Koza and Lewin 1999).

Even though it is recognized that explicating the dynamic interplay between an organization's internal resource base and external network is important to better understand the organization-environment link (Baum and Singh 1994, Gulati and Gargiulo 1999), research on the subject is still in its infancy. The present paper contributes to this research objective by examining whether and how an organization's technological knowledge – a critical component of its resource base – coevolves with the organization's R&D alliance network. While the arguments developed in the paper are solidly grounded in previous research, we depart from extant literature in two significant ways. First, prior studies predominantly posited a unidirectional causal relation whereby an organization's R&D

network position affects its technological knowledge base (Schilling and Phelps 2007), or vice-versa (Rothaermel and Boeker 2008). By contrast, a theoretical contention of the present study is that such relation is inherently bidirectional. Second, most studies on R&D networks focused on a single technological sector (Powell et al. 1996). However, recent research shows that technological sectors develop in an ecologically interdependent fashion (Carnabuci, 2010) and that a large share of R&D alliances cut across sectorial boundaries (Schilling 2009). To understand how an organization's knowledge base and external network coevolve, it is therefore critical to expand consideration to the entire network of R&D alliances connecting organizations throughout the technological landscape. Consistent with this view, the second distinguishing aspect of this study is that it focuses on a complete network of R&D alliances both within and across technological sectors.

To examine the co-evolutionary dynamics linking organizations' knowledge and network position, we focus on and integrate two well-established but thus far largely unrelated lines of inquiry. To characterize organizations' knowledge base, we draw on the distinction between *technological specialists* – whose technological knowledge yields the greatest returns when applied to a narrow niche of application sectors, and *technological generalists* – whose technological knowledge yields the greatest returns when applied to a broad range of application sectors (Arora et al. 2001, Gambardella and McGahan 2010, Mitchell and Singh 1993, Owen-Smith et al. 2002). To characterize organizations' external networks, we consider whether a firm occupies a *core* or a *peripheral* position within the R&D alliance network. The key contention of the paper is that moving towards the core (periphery) of the R&D network induces organizations to develop a generalist (specialized) knowledge base. At the same time, developing a generalist (specialized) knowledge base induces organizations to move towards the core (periphery) of the R&D network. The combined effect of these mechanisms implies a self-reinforcing dynamics whereby the internal knowledge base of an organization systematically coevolves with its position in the external R&D network.

To support this co-evolutionary hypothesis, we proceed as follows. We begin by developing the argument that an organization's position in the structure of the R&D network, defined in terms of a continuum from core to periphery, influences whether the organization will develop a specialized or a generalist knowledge base. In particular, we articulate this hypothesis by arguing that an organization's network position shapes both its interests structure (which type of technological knowledge an organization *prefers* to develop) and its opportunity structure (which type of technological knowledge an organization *is able* to develop). Applying this same explanatory logic to the reverse causal relation, we then argue that the degree of specialization (generality) of a firm's knowledge affects both its interests structure (which R&D collaboration ties an organization prefers to develop) and its opportunities structure (which R&D collaboration ties an organization is able to develop)[1]. We then move into describing the setting, data and econometric approaches used to test our arguments. We conclude by discussing how the results of the study change our understanding of the relation between organizations' knowledge and networks and, more broadly, between organizations and environments.

Core and periphery in R&D alliance networks

Core-periphery structures have been found to be ubiquitous and "substantively important" in a variety of empirical settings (Mullins et al. 1977, White et al. 1976, p. 742, Zelnio 2011), and especially in the context of inter-organizational networks (Cattani and Ferriani 2008, Connelly et al. 2011, Mintz and Schwartz 1981). Core-periphery structures are characterized by a cohesive clique of densely interconnected core actors surrounded by a fringe of weakly connected peripheral actors (Borgatti and Everett 1999, p. 375). Figure 1 presents an illustration. The densely tied hollow squares at the center of the network represent the core. Peripheral actors, represented by the dark circles at the outskirts of the network, are connected to the network through fewer and mostly indirect connections. Thus, reflecting the sociological intuition that core actors mutually reinforce each other's structural position (Snyder and Kick 1979), an actor's coreness is recursively defined by the coreness of the actors it is tied to: the more ties a focal actor has with contacts who themselves are tied to core actors, the closer is the focal actor to the network core (Borgatti and Everett 1999).

A long-standing tenet among network researchers is that due to their structural position, core actors tend to "play the key coordinating roles…whereas the periphery is occupied by actors with less integrative importance" (Knoke et al. 1996, p. 23). Consider the position of node A and node B in

[1] To simplify our exposition, let us stipulate that in the remainder "specialization" signifies the opposite of "generality" (and the adjective "specialized" signifies the opposite of "generalist"), and vice-versa. Similarly, let us stipulate that "core" signifies the opposite of "periphery" (and "peripheral"), and vice-versa.

Figure 1, representing a core and a peripheral actor, respectively. A's network position differs from B's in two important ways, pertaining to the structure of both *direct* and *indirect* connections in which the two actors are embedded. First, A is directly tied to a large number of densely interconnected core contacts. B, on the other hand, is directly connected to a couple of core actors but is otherwise isolated. Second, shifting the focus to actors' indirect connections shows that A is at a relatively close distance from virtually all nodes in the network. B, conversely, is several steps away from the vast majority of other peripheral nodes, which it can only reach via the core[2]. Whether one looks at actors' local network of direct connections or at their broader network of indirect ties, therefore, A's network position encompasses a wider and structurally more heterogeneous array of contacts than B's. Hence the network argument that A is generally in the position to integrate and coordinate a broader range of contacts (and thus of knowledge, resources and opportunities) than does B (Knoke et al. 1996).

The integrating role of core organizations is especially evident in the context of our empirical setting – the evolving network of R&D alliances formed among US-based firms, both within and across technological sectors. R&D alliances represent formal collaborative agreements involving exchange, sharing, or co-development of technologies and services (Zhang et al. 2007, p. 515). Thus, on the one hand R&D alliances represent a prime source of learning for the organization, facilitating the absorption of both tacit and codified technological knowledge from one's partners (Dyer and Nobeoka 2000, Kale and Singh 2000, Powell et al. 1996). On the other hand, through R&D alliances firms can mobilize knowledge, resources complementary assets both upstream and downstream, including functional capabilities in critical areas such as new product development, marketing, and distribution (Arora and Gambardella 1990, Grant and Baden-Fuller 2004, Rothaermel and Boeker 2008). Hence, organizations embedded within the core of the R&D network have the potential to acquire knowledge and to utilize resources and complementary assets from across a wider portion of the technological landscape. Conversely, the more peripheral an organization's position in the R&D network, the narrower and more structurally homogeneous the set of direct and indirect contacts from

[2] Consider the following statistics. A can reach 97% of the nodes within just two steps while for B, only half of the network is reachable within 2 steps. At a global network level, the sum of geodesic distances (i.e., the shortest number of steps) it takes B to reach every other network node is roughly 60% larger than it is for A. Lastly, 100% of the geodesics (i.e., the shortest paths) through which B reaches out to other nodes go through the core.

which it can potentially acquire knowledge and draw resources. These arguments are summarized by the following proposition.

Proposition 1: Through their direct and indirect contacts, organizations positioned in the core of the R&D network can reach out to a greater portion of the technological landscape. As a result, *(a)* they can mobilize knowledge, resources and complementary assets from across a wider set of technological sectors compared to peripheral organizations; *(b)* they are exposed to and absorb knowledge stemming from a wider range of technological sectors than peripheral organizations.

A key contribution of the inter-organizational network literature is that because core organizations have greater integrating potential than peripheral ones, an organization's position along the core-periphery continuum deeply shapes the structure of interests and opportunities the organization is faced with (Knoke et al. 1996). As we will elaborate below, a specific hypothesis that can be derived from this general argument is that core organizations tend to preferentially attract, and to be attracted to, R&D partners characterized by a generalist technological knowledge, while peripheral organizations preferentially form R&D alliances with technological specialists. Before we articulate this argument, however, it is important to explain the difference between technological generalists and technological specialists and why such difference impinges on the alliance formation process.

Technological generalists and technological specialists

While many aspects of an organization's knowledge base have been shown to impact critical organizational outcomes (Yayavaram and Ahuja 2008), one aspect that has drawn particular attention is the distinction between generalist and specialized technological knowledge bases (Arora and Gambardella 1990, J. M. Mezias and S. J. Mezias 2000, Mitchell and K. Singh 1993, Zhang et al. 2007). An organization is a technological generalist insofar as its technological knowledge can be turned into economically valuable products or services across a wide range of application sectors; conversely, it is a technological specialist if its technological knowledge can be usefully applied only within a narrow range of application sectors (Bresnahan and Trajtenberg 1995)[3]. Thus, an ideal-

[3] The distinction between technological generalists and technological specialists is grounded in one of two widely debated assumptions (Rosenberg 1994). A first, stronger assumption is that a firm's accumulated

typical technological generalist is a firm whose knowledge base is anchored in a "general purpose technology," such as mobile data communication technologies or security software technologies, which it can adapt at a relatively low cost to serve multiple application sectors or market segments. At the opposite end, a pure technological specialist is a firm whose knowledge can be usefully applied to only a narrow and well-defined set of applications (Bresnahan and Trajtenberg 1995, David 1990, Gambardella and Giarratana forthcoming, Moser and Nicholas 2004, Rosenberg and Trajtenberg 2004). Early producers of numerical control machines represent a case in point, as the value of their technological knowledge was entirely specific to a thin range of applications within either the aerospace or the automobile industry (Bresnahan and Gambardella 1998).

The distinction between generalist and specialized knowledge bases is theoretically important because generalists and specialists face a fundamentally different interest and opportunity structure. As Gambardella and McGahan pointed out (2010, p. 265), "the innovator focuses on maximizing the number of high-value applications that may involve its technology, which it can affect by investing in skills, resources and capabilities." Because their technological knowledge is more widely applicable, technological generalists have an incentive to maximize scope economies by expanding the range of application sectors served even if this means undergoing the benefits of specializing in any specific application sector (Miller, 2004). An example is Universal Oil Products (UOP), a company that built its distinctive knowledge base around the so-called Dubbs process: a general method for continuous cracking of *any* kind of oil. In what turned out to be a remarkably successful strategy, UOP never attempted to become a specialist in any of the application sectors it served. Rather, it kept developing ways to redeploy its technological knowledge across ever new applications sectors. As a result, "UOP has been able to assemble a combination of processing 'blocks' that would allow a producer to make any combination and relative quantity of benzene, toluene, and xylene isomers from any conceivable

technological knowledge defines the range of possible applications the firm can and cannot develop. A second, weaker assumption is that a firm's knowledge merely affects the cost-benefit structure associated with alternative technological developments. Thus according to this second assumption, the technological knowledge of a generalist is such that it is advantageous for the firm to develop applications across a wide range of application sectors, while the opposite is true for technological specialists. As will become clear in the following pages, this weaker assumption suffices for our theoretical argument.

feedstock," resulting in huge scope economies and an undefeatable competitive position (Bresnahan and Gambardella 1998, p. 265).

While maximizing the breadth of applicability of their knowledge base is advantageous for technological generalists, the situation is reversed for technological specialists. As their knowledge base is characterized by limited generality, pursuing scope economies by developing applications across new application sectors would be exceedingly costly. On the other hand, their narrow focus puts them in a better position to exploit the advantages of technological specialization relative to generalist firms. "An inherent tension in any division of labor is that the distinct users of a technology, or for that matter of a good or service, employ it for different purposes. Consequently, they have different needs, and these needs would be best satisfied by producing, adapting, or using the technology or input according to their special goals and demands" (Bresnahan and Gambardella 1998, p. 255). Due to the narrow applicability of their knowledge base, technological specialists thus have an incentive to deepen penetration and develop superior technological offerings within a limited set of applications, even if this comes at the cost of undergoing potential scope economies. These arguments lead to the following proposition.

Proposition 2: The greater the generality of an organization's technological knowledge base, the stronger its incentive to exploit scope economies by maximizing the breadth of application sectors served.

Technological generality, network coreness, and R&D alliance formation

What drives the formation of R&D alliances? Providing insight into this question, Mitsuashi and Greve (2009, p. 975) argued that "[a]lliance formation is a selective process in which organizational characteristics influence the likelihood of participation and the specific pairings that result". In line with this view, prior research has conceptualized the formation of R&D alliances as a matching process whereby two organizations are more likely to ally if they both expect to gain from combining their own knowledge, resources and complementary assets with the knowledge, resources and complementary assets controlled by the partner organization (e.g., Rothaermel and Boeker 2008).

A specific implication of this argument, we suggest, is that technological generalists are more likely than technological specialists to form R&D alliances with organizations positioned within the core of the R&D network. An organization's position along the core-periphery structure of the network may affect the alliance formation process because an organization's attractiveness as a potential R&D partner does not only reflect the knowledge, resources and complementary assets it owns, but also those that it can *mobilize* through its alliance network (Lavie 2006, Zaheer and Bell 2005). From this perspective, core organizations represent an R&D partner that is ideally suited to pursue technological generalists' preferred strategy, i.e., to reap scope economies by broadening the range of application sectors in which their generalist knowledge base can be deployed. As stated in proposition 1a, through their alliance network core organizations can reach out to a much wider portion of the technological landscape, relative to peripheral organizations. As a result, they are in a stronger position to mobilize knowledge, resources and complementary assets that may help technological generalists to convert their knowledge into economically valuable products, services and technologies across many application sectors. By a similar logic, core organizations should have a stronger incentive to form R&D alliances with technological generalists than with technological specialists, because the former are better equipped to maximize the value inherent in their network position. Although forming an alliance with a technological specialist may provide superior offerings within a specific and well-circumscribed application sector, allying with a generalist R&D partner is more likely to yield spillovers and opportunities throughout the dense but far-reaching alliance portfolio characteristic of core organizations. In line with selective matching process described above, we therefore posit that technological generalists are more likely than technological specialists to form R&D alliances with organizations embedded within the core of the R&D network.

Proposition 3: The greater the generality of an organization's technological knowledge base, the more likely is the organization to form R&D alliances with partners positioned in the core of the R&D network.

The coevolution of organizations' knowledge base and network position

The key contention of this paper is that the degree of generality of an organization's knowledge base co-evolves with the organization's position along the core-periphery structure of the R&D alliance network. This argument postulates a two-way causal dynamic. First, the more an organization develops a generalist knowledge base, the more it will move towards the core of the R&D network.

Second, the more an organization moves towards the core of the R&D network, the more it will develop a generalist knowledge base. We now explicate each of these theoretical claims in turn.

As illustrated by Figure 1, an organization's position along the core-periphery structure of the R&D network reflects the pattern of alliances it establishes with other organizations. Specifically, a focal organization's coreness is recursively defined by the coreness of the organizations with which it allies: the more R&D alliances a focal organization forms with partners positioned in the core of the R&D network, the more the focal organization will move towards the core (Borgatti and Everett 1999). Combined with this simple mechanism of network dynamics, a straightforward implication of Proposition 3 is that expanding the generality of an organization's knowledge base increases the likelihood that an organization will form R&D alliances with core partners and, hence, that it will move towards the core of the R&D network. By implication, the more specialized an organization's knowledge base becomes, the more the organization will drift towards the network periphery.

> **Hypothesis 1**: The greater the generality an organization's technological knowledge base, the more the organization will move towards the core of the R&D alliance network; the more specialized an organization's technological knowledge base, the more the organization will move towards the periphery of the R&D alliance network.

The arguments developed thus far suggest two reasons why this causal relation may run in the opposite direction, too. First, even though an organization's technological knowledge accumulates in a path-dependent fashion (Cohen and Levinthal 1990), firms may steer its development through R&D investment decisions aimed at seizing the value inherent in their unique knowledge base (Gambardella and McGahan 2010, Scherer 1965). As stated by Proposition 1a, core organizations are in a better position than peripheral organizations to mobilize knowledge, resources and complementary assets across multiple application sectors, either by tapping directly from their R&D partners or through their partners' intermediation. For that reason, it is in their best interest to develop technological knowledge that can be converted relatively easily into valuable products, technologies or services across a wide variety of application sectors. Hence the closer an organization is to the core of the R&D network, the stronger should be its incentive to increase the generality of its technological knowledge base. Conversely, investing in developing generalist technological knowledge is less attractive for peripheral organizations, as their network position does not grant them access to the knowledge, resources and complementary assets necessary to fully exploit its value.

Second, in addition to having an incentive to do so, core organizations may tend to systematically broaden the generality of their knowledge base because, as stated by Proposition 1b, the knowledge accruing to core organizations comes from direct and indirect contacts scattered throughout a much wider portion of the technological landscape compared to peripheral organizations. Hence, core organizations are likely to absorb knowledge stemming from diverse technological sectors, while peripheral organizations are likely to be exposed to a more homogeneous knowledge environment. These arguments lead us to our second hypothesis:

> **Hypothesis 2:** The closer is an organization to the core of the R&D alliance network, the more the organization will develop a generalist technological knowledge base; conversely, the closer is an organization to the periphery of the R&D alliance network, the more the organization will develop a specialized technological knowledge base.

As it appears, the combined effect of hypotheses 1 and 2 implies a self-reinforcing causal dynamics whereby the internal knowledge base of an organization systematically coevolves with its position in the external R&D network. Next we discuss the data and methods used to put this argument to a rigorous empirical test.

Data, measures, and methods

As argued above, a large share of R&D alliance ties cut across technological boundaries (Schilling 2009). Hence, capturing the co-evolution of organizations' knowledge base and network dynamics requires us to collect information on all R&D alliances, not just those confined within sectorial boundaries. To this end, we collected data on all R&D alliances, in any industrial or technological sector, registered with the US Department of Justice under the National Cooperative Research Act (NCRA) between 1985 and 2003. Our data is similar to that reported in the CORE database in that both are drawn from filings reported in the Federal Register. A key strength of using the Federal Register as a source of R&D alliance data is that it allows us to "capture a complete population – all of the collaboration agreements filed under the NCRA Act…[which] has some important inference advantages over the other datasets" (Schilling 2009, p. 237). Unlike the CORE database, we obtained and tracked membership in the various research joint ventures (RJV) at the organization and arrangement level. Because there may be inconsistencies in naming of organizational members across Federal Register filings, and because collecting homogeneous and reliable organization-level data among non-public firms is almost impossible, we limit our analysis to publicly traded firms in the US. This results in a final sample of 762 organizations for a total of 4941 organization-year observations, with the average organization being in 6.5 R&D consortia over the observation period. In addition to R&D alliance data, we collected two additional types of longitudinal data. First, we obtained yearly financial and organizational measures from Standard and Poor's *Research Insight*. Second, we collected all patents granted to each firm by the USPTO (United States Patent and Trademark Office), in any technological sector, throughout the observation period. To trace the time at which a patent was filed by the organizations in our sample, we used the patent filing date. The patent data was collected from Bronwin Hall's website, who updated the NBER original patent dataset (Hall et al. 2001) up to year 2004 as part of the NBER project. We combined these three data sources to measure our dependent and independent variables, which we describe next.

Dependent variables

Coreness: The degree of coreness of an organization within the R&D network is measured following Borgatti and Everett (1999). The authors propose a continuous model in which each node is assigned a measure of coreness representing how close they are to the core (and hence how far they are from the periphery) of the network. The choice to measure coreness as a continuous variable derives from our theoretical conceptualization, which was premised on the view that organizations' network position varies along a core-periphery continuum. Furthermore, the network data we collected allows us to represent the strength of R&D relationships as valued ties, rather than one-zero dichotomies, where strength reflects the number of current R&D alliances between any pair of organizations at any point in time. Borgatti and Everett (1999) propose the following model to define the coreness of each organization in the network:

$$C_{ij}=c_i c_j \qquad (1)$$

where $\boldsymbol{C}$ "…is a vector of nonnegative values indicating the degree of coreness of each node. Thus, the pattern matrix has (i) large values for pairs of nodes that are both high in coreness, (ii) middling values for pairs of nodes in which one is high in coreness and the other is not, and (iii) low values for pairs of nodes that are both peripheral". The values in ***C*** are estimated empirically through an algorithm that "finds a set of values c_i such that the matrix correlation between c_i and c_j and the data matrix is maximized" (Borgatti and Everett 1999, p. 387). The algorithm allows one to measure the coreness of nodes whether or not they belong to the largest component. Conventionally, the coreness of isolate nodes is set to zero to signify that their distance from the core is largest. Because bounded variables violate critical assumptions underlying least squares regressions, we followed established practice and linearized our measure of coreness by taking its logit transform.

Knowledge Base Generality: To measure how general is the technological knowledge base of an organization, we constructed a measure of generality following an established approach in the innovation literature. Namely, we took all successful patent applications filed in a given year by each firm in our population. Then, following Trajtenberg et al. (1997) and others (e.g, Argyres and Silverman 2004, Chatterji and Fabrizio 2012), we tracked the pattern of forward citations of each of those patents, allowing us to assess whether they represent general-purpose or specialist technological knowledge. In particular, we first calculated the degree of generality of each patent as follows:

$$Pi = 1 - \sum_{j=1}^{n} s^2{}_{ij} \qquad (2)$$

where s_{ij} indicates the proportion of citations received by patent *i* that belongs to patent class *j*, out of the n_i patent classes from which *i* received citations (time subscripts are omitted for the sake of simplicity). Therefore, if patent *i* is cited by subsequent patents that belong to a wide range of technological fields the measure will be high, whereas if most citations are concentrated in a few fields the measure of generality will be close to zero. Building on this patent-level measure of generality, we then calculated the generality of firm *k*'s knowledge base as the average generality across all of *k*'s patents, *z*, in a given year[4]:

[4] As also this measure is bound between zero and one, we linearized it by taking its logit transform. For both Coreness and Knowledge Base Generality, we replaced zeros by 0.0001 and ones by 0.9999 to avoid losing observations through the logit transformation. As a robustness check we tried several alternative values. As we explain in detail in the Additional Analysis section, we also measured Knowledge Base Generality using two alternative measures. The results of our analyses proved to be consistent under all these robustness checks.

$$\mathbf{G_k} = \sum_{i=1}^{z} \frac{P_i}{Z} \qquad (3)$$

Independent variables

We used a number of variables obtained from Standard & Poor's Research Insight database, whose effects we aim to control for. We controlled for firms' *Total assets***,** measured as the sum total of all assets of a firm in a given year, because organizations with greater total assets tend to be more resourceful. Hence, one might reasonably argue that the total assets of a firm may positively impact both their generality and their coreness. Similarly, we controlled for the total number of *Employees* of each firm in each year, as this provides a widely used measure of organizational size. Also, we measured firms' *R&D cost per employee* to control for the fact that some organizations are more R&D-intensive than others. Given our emphasis on the role of knowledge as a driver of R&D alliance formation, controlling for R&D intensity is important to ensure that the effects we observe can be ascribed to our variable of theoretical interest. In models not reported here, we controlled for a wider set of factors including firms' intangible assets, advertising costs, and financial performance**.** These variables created multi-collinearity, though, and were therefore excluded from the final models.

Instrumental variables

Because we hypothesized our two dependent variables to be endogenously related, we also constructed a set of instrumental variables to help us tease out the effects postulated by our theory. Constructing a valid instrument set allows one to exploit only the exogenous variation in a regression equation, making it possible to correctly estimate causal effects even in the presence of endogeneity. Instrumental variables are valid if they meet both a "relevance" criterion (i.e., they have a significant impact on the endogenous regressor) and an "exogeneity" criterion (i.e., they do not directly affect the dependent variable of the structural equation and, hence, are uncorrelated with the disturbance term). We selected two instrumental variables for each endogenous variable because this allowes us to run a comprehensive set of diagnostic analyses to test the validity of the instruments. In what follows we present the theoretical rationale that guided our choice of instruments; in the results section we will discuss the formal tests carried out to assess the validity of the instruments.

We used a major earthquake occurred in the San Fernando Valley at Northridge (California) in January 1994, to instrument organizations' coreness. With total damages estimated at $44 billion[5], the devastation caused by the *California Earthquake* had a severe impact on the state's infrastructure. What is crucial here, the earthquake resulted in major damages to the physical infrastructure supporting Californian R&D activities by temporarily breaking down or severely impairing business organizations' R&D sites, supply networks, and communication systems (Toh 2007). As a result, we expect the Northridge earthquake to have reduced the ability of Californian firms to initiate or continue R&D collaborations (Toh 2007) and, hence, to have temporarily diminished those organizations' coreness in the global R&D network. Further, we expect the Northridge earthquake to be a suitable instrumental variable because, in addition to representing an undoubtedly exogenous shock affecting the coreness of Californian firms, it is unlikely to have affected those organizations' tendency to generate specialized versus generalist technological knowledge.

We used *State Property Net Subsidies* as a second instrumental variable for Coreness. This variable comes from the NBER Taxsim (http://users.nber.org/~taxsim/) database and it captures differences in tax deduction regimes for property of land and buildings. It is computed for every year and state and is expressed as the number of dollar cents that are deductible for any additional dollar of property taxes owed. As land and buildings are an important part of the physical infrastructure supporting R&D activities, we reckoned that such net subsidies would increase a firm's ability and propensity to form R&D alliances and, hence, to move towards the core of the R&D network. However, we do not expect such subsidies to directly influence the degree of generality or specialization of an organization's technological knowledge base.

To instrument our second dependent variable – Knowledge Base Generality – we exploit a technological shock occurred in the mid-nineties, which profoundly changed the knowledge profile of firms operating in the information technology sector: the rise of the internet. While the inception of the internet can be traced back to the ARPANET backbone developed in the late 1970s, it is only by the mid-1990s that the number of internet hosts and regional network access points grew explosively,

[5] OES (California Governor's Office of Emergency Services) (1997). "The Northridge Earthquake of January 17, 1994: Report of Data Collection and Analysis, Part B: Analysis and Trends", Irvine and Pasadena, EQE International and Office of Emergency Services. Cited in (Toh 2007).

unleashing a huge economic potential unforeseen even by practitioners and technology experts. Complementing a detailed quantitative analysis of the internet shock, Schilling (2011, p. 7) reports two evocative quotes that give a sense of how the perception of the internet changed in less than two years: *"Let's face it. Not many members of the public -- even the computer literate public - are on the Internet"* (John Goodwin, a tutorial for the internet, July of 1993); *"Businesses and entrepreneurs are rushing into cyberspace like forty-niners driven mad by gold fever"* (Vic Sussman and Kenan Pollack, U.S. News and World Reports, November of 1995).

Due to its sudden and unforeseen nature, numerous studies have characterized the internet explosion peak of the mid-1990s as a "technology shock" (Schilling 2011). The epicentre of this shock was in the information technology sector, where the internet acted as a "general purpose technology" that pushed organizations to dramatically expand their knowledge base so as to be able to adapt their offerings to a much wider range of application sectors. Consistent with this reconstruction we constructed a variable, labelled *IT Internet Shock*, which we used to instrument organizations' knowledge base generality. The variable is set to 1 if an observation (i) pertains to a firm belonging to the Information sector according to the NAICS classification system and (ii) is recorded between 1994 and 1996; it is set to zero otherwise.

In addition to IT Internet Shock, we instrument organizations' generality through a second variable, *Effective Size*, which captures the structural holes brokered by an organization at any given point in time (Burt 1992, pp. 52–57). Because organizations embedded in structural holes are exposed to a heterogeneous set of mutually unconnected R&D partners (Ahuja 2000b), we expected organizations' effective size to have a positive impact on organizations' generality. However, we do not see any reason why Effective Size should impact organizations' Coreness.

Results

Descriptive analyses

Figure 2 describes how the R&D alliance network analyzed in the study changed over the observation period. The figure shows that the number of organizations that registered at least one R&D alliance peaked around year 2000 reaching nearly one thousand organizations, and then dropped quite dramatically immediately after. Similarly, the total number of R&D alliances observed in the study population approached its maximum in year 2000, which also corresponded to a peak in the total volume of R&D investments incurred by the organizations participating in the network. Inspecting the data at a more microscopic level allows us to gain further insight into these aggregate trends. In particular, it is interesting to notice that the number of registered R&D consortia peaked and then began to decline in 1995-1996, hence a few years earlier than year 2000. However, this decline was partly countervailed by two factors occurring at the same time. On the one hand, the average size of R&D consortia, which had reached its minimum in 1995 with just about two organizations per consortium on average, began to rise again starting in 1996 and continued until the end of the observation period. As a result, at the end of the observation period the average R&D consortium comprised as many as 4.5 organizations, while the average number of R&D alliances per organization was at its peak. On the other hand, the average R&D investment of the organizations belonging to the network began to grow in the same years, and the growth further steepened after year 2000. Consistent with this pattern of results, a closer inspection of the data shows that the *composition* of the network changed after 1995-1996, meaning that the organizations that exited the network were less R&D intensive than those that stayed or entered it.

Overall, these analyses point to a few important patterns characterizing the evolution of the R&D alliance network examined in this paper, which can be summarized as follows. Around year 2000 the R&D alliance network began to rapidly shrink as testified by a decline in (a) the total number of organizations in the network, (b) the total number of R&D alliances connecting those organizations and (c) the total volume of R&D investments made by those organizations. If one looks more closely at the micro-structure of the R&D network, though, it also becomes apparent that the composition of the R&D alliance network began to change in 1995-1996: compared to the organizations that remained in or entered the network, the organizations leaving the network featured (d) a lower average R&D investment level and (e) entertained fewer R&D alliances.

-----------------------------------FIGURES 2-3 ABOUT HERE---------------------------------

Because our arguments rest on the notion of coreness, it is important to demonstrate that the observed R&D network has a core-periphery structure – and that this structure is robust to the structural and composition changes just described. As mentioned earlier, a core-periphery structure consists of a cohesive clique of densely interconnected core actors surrounded by a fringe of weakly connected peripheral actors, as exemplified by Figure 1. Borgatti and Everett (1999) developed a model that quantifies, through a parameter comprised between zero and one, the extent to which an observed network conforms to such a structure; Figure 3 shows how this parameter changes over the observation period for our R&D alliance network. The graph shows two important things. First, the R&D alliance network has a distinctive core-periphery structure, with values ranging from a minimum of 0.58 to a maximum of 0.9 and an average value of 0.73. While there is no clear-cut threshold to establish whether a network has a core-periphery structure, previous work has considered an average 0.55 value to represent an acceptable fit level (Cattani and Ferriani 2008). Second, the network preserved a robust core-periphery structure in the face of the structural and compositional changes described above, reaching an almost complete fit towards the end of the observation period.

Econometric analyses

Table 1 provides means, standard deviations, and correlations among the variables used in the model. Table 2 presents the results of several panel regression specifications used to test our hypotheses. We begin by noticing that multicollinearity does not represent a problem: across the twelve models reported in table 2, the highest individual-variable VIF is 4.45 while models' mean VIFs range from 1.10 to 2.72, well within conventional acceptability levels. Table 2 presents two sets of models: those denoted by (a) predict Knowledge Base Generality; those denoted by (b) predict Coreness. Within each set, we report results obtained under four alternative estimators (OLS with fixed effects, 2SLS with fixed effects, 2SLS with first-differenced variables, 3SLS with fixed effects) and two alternative lag structures (contemporaneous and one-year lagged).

--------------------------------TABLE 1 ABOUT HERE---

Under the hypothesis that Knowledge Base Generality and Coreness are endogenously related, as our theory postulates, the OLS estimator yields biased estimates. Since most published work on the effects of inter-organizational networks on organizations' knowledge-based outputs (or vice-versa) use the OLS fixed-effects estimator, however, we report coefficient estimates obtained with the same approach in models 1a through 2b of table 2. The remaining eight models are based on a system of equations of the following general class:

$$y_{it} = a_1 + b_1 x_{it} + i_1 r_{1it} + c_1 z_{it} + d_1 k_i + f_1 h_t + e_{1it}$$
$$x_{it} = a_2 + b_2 y_{it} + i_2 r_{2it} + c_2 z_{it} + d_2 k_i + f_2 h_t + e_{2it} \qquad (4)$$

where h_t represents unit-invariant time-varying factors; k_i models firm fixed effects; y_{it} and x_{it} measure an organization's coreness and technological generality, respectively; z_{it} is a set of control variables common to both equations; r_{1it} is a set of excluded instrumental variables for x_{it}; and, r_{2it} is a set of excluded instrumental variables for y_{it}. All variables on the right-hand side are assumed to be exogenous with the exception of x_{it} in the first equation and of y_{it} in the second. This model assumes y_{it} and x_{it} to be endogenously related, as postulated by our theory, yielding efficient and unbiased estimations even in the presence of endogeneity (Wooldridge 2002). Within this general framework, models 3a through 5b employ a 2-stage Least Square estimator (2SLS), whereby the error terms e_{1it} and e_{2it} are assumed to be independently and identically distributed within each equation but uncorrelated across equations. Specifically, models 3a and 3b report 2SLS estimates based on a fixed effects estimator and contemporaneous effects, while in models 4a and 4b all right-hand side variables are lagged one year. Models 5a and 5b, on the other hand, report 2SLS estimates based on first difference transformations. Insofar as e_{1it} and e_{2it} are uncorrelated across equations, and the instruments used in the first stage are relevant and valid, all three specifications of the 2SLS estimator yield unbiased estimates. If e_{1it} and e_{2it} are correlated across equations, however, a 3SLS estimator provides a superior solution as it allows the error structure of the equations to co-vary. Models 6a and 6b use a 3-Stage Least Square estimator (3SLS), which extends the 2SLS estimator by allowing for e_{1it} and e_{2it} to be correlated across equations. Testing our hypotheses through this set of complementary econometric specifications is important both in order to assess the robustness of our results and in order to examine our causality claims in a precise and granular fashion.

------------------------------------TABLE 2 ABOUT HERE--

Let us now to turn the results. As said, our hypothesis is that a two-way causal relationship links the degree of coreness of an organization within the R&D network and the generality of the organization's technological knowledge base. A logical implication of this argument is that Coreness is an endogeneous regressor of Knowledge Base Generality, and vice-versa. To test whether this is the case, we performed a set of pair-wise Hausman tests comparing models where the suspect endogenous variable is treated as endogenous, with an equivalent model where it is treated as exogenous. Under the null hypothesis that the suspect endogenous variable is exogenous, the test statistic is distributed as chi-squared with degrees of freedom equal to the number of regressors tested. Hence if the null hypothesis is rejected, the variable in question is in fact endogenous. The results of the test, reported at the bottom of table 2, show that the null hypothesis is rejected across all 2SLS models. This finding supports our theoretical expectation, as it implies that Coreness and Knowledge Base Generality are endogenously co-determined.

To test the causal effect of Coreness on Knowledge Base Generality, and the reverse causal effect of Knowledge Base Generality on Coreness, we therefore need a valid instrument set for each endogenous regressor. As explained above, we selected California Earthquake and State Property Tax as instruments for Coreness, while Internet IT Shock and Effective Size were chosen as instruments for Knowledge Base Generality. Assessing the validity of these instruments amounts to testing whether they meet both the "relevance" and "exogeneity" criteria. We carried out three standard econometric tests to assess whether both conditions are met by our chosen instrument sets. First, the Anderson canonical correlations under-identification test is a test of whether the excluded instruments are "relevant," that is, correlated with the endogenous regressor (Anderson 1984). A rejection of the null hypothesis in this test indicates that the model is identified, hence the chosen instrument set has a significant impact on the endogeneous regressor. Second, the weak identification test (Cragg and Donald 1993) extends the under-identification test by examining whether the excluded instruments, even if correlated with the endogenous regressor, may result in an ill-identified model because the impact of the instruments is too weak. A rejection of the null hypothesis in this test means that the chosen instrument set has a sufficiently large impact on the endogenous regressor, yielding a correctly identified model. Third, we performed a Sargan-Hansen test of over-identifying restrictions to assess whether the instruments are exogenous, that is, uncorrelated with the error term in the structural equation. A rejection of the null hypothesis in this test signals that the chosen instruments may have been incorrectly excluded from the estimated equation and hence may not be valid (Hayashi 2000). The three tests are reported at the bottom of table 2. The results show that the chosen instruments are valid according to all three tests in all 2SLS specifications, implying that the reported models yield consistent and unbiased coefficient estimates.

Let us now turn our attention to the coefficient estimates. We begin by noticing that both the sign and significance level of our variables of theoretical interest are stable across all twelve models. Hypothesis 1 predicted that the higher is the generality of an organization's technological knowledge base the more the organization will tend to move towards the core of the R&D alliance network. Conversely, the higher is the specialization of an organization's technological knowledge base the more it will move towards the periphery of the R&D network. Corroborating this hypothesis, Knowledge Base Generality has a positive and highly significant effect on Coreness in all models. Hypothesis 2 predicted that the closer is an organization to the core of the R&D alliance network the more it will increase the generality of its technological knowledge base; by contrast, the more peripheral a firm's network position the more technologically specialized it will become. In line with this prediction, Coreness has a positive and highly significant effect on Knowledge Base Generality in all models. While demonstrating claims of causality is inherently difficult, these results do lend strong support for the hypothesis of a two-way causal relation linking the degree of generality of an organization's knowledge base and its position in the R&D network.

Inspecting the results obtained under each alternative model specification provides further insight into this self-reinforcing causal link. First, the results suggest that both causal effects – generality affecting coreness and coreness affecting generality – have a sizeable impact that explains a fair share of the observed variance, suggesting that these causal mechanisms are not merely *statistically* significant. Caution must always be used when interpreting coefficients in the context of instrumental variable regressions. Furthermore, interpreting Knowledge Base Generality and Coreness is complicated by the fact that both variables are expressed as logit transformations. With these caveats in mind, one useful approach is to conceive of the coefficients of Knowledge Base Generality and Coreness as representing elasticities of the two following ratios: Generality-to-Specialization and Core-to-Periphery. Interpreted this way, models 2a and 2b indicate that a 1% increase in the Coreness-to-Periphery ratio yields a 5.7% increase in the Generality-to-Specialization ratio; conversely, a 1% increase in the Generality-to-Specialization ratio generates a 2.3% increase in the Coreness-to-

Periphery ratio. Second, Coreness appears to have a stronger impact than Knowledge Base Generality across all model specifications, suggesting that the causal relation between the two is bidirectional but asymmetric. Third, even though both effects are still strong and highly significant after one year, as testified by models 3a and 3b, they appear to exert the strongest impact within the first year. Confirming the relevance of such short-term causal effect, models 4a and 4b use a first-difference estimator to show that a *change* in the degree of Coreness (Knowledge Base Generality) of a firm from one year to the next, results in a sizeable and statistically significant *change* in the Knowledge Base Generality (Coreness) of that same organization over the same time span.

Moving to the control variables, our results show that firms with greater Earnings per Share tend to increase the generality of their technological knowledge base while at the same time they tend to move towards the periphery of the R&D alliance network. Conversely, larger organizations (i.e., organizations with more employees) develop more specialized knowledge bases and they tend to move towards the core of the R&D network – a pattern that, while less stable, appears to also characterize knowledge intensive organizations (i.e., organizations with a higher R&D cost per employee). Interestingly, these findings suggest that the self-reinforcing causal loop between knowledge base generality and network coreness is not left undisturbed in the context of our study but, rather, it is mitigated by factors such as organizations' profitability and size. This consideration is important because, in the absence of such interfering influences, our co-evolutionary theory would lead to the unlikely implication that all generalist organizations will sooner or later end up in the network core, while the network periphery should only comprise technological specialists. Lastly, there is some evidence that organizations' knowledge base and network position have been partly affected by unit-invariant time effects. In particular, organizations generally developed more specialized technological knowledge between 1985 and 1990 (1997-2002 is the reference category) while during those same years organizations' average coreness appears to have reached a high point. Although the results obtained in the first-stage equations are not fully reported here, it is worthwhile noticing that the effects of the instrumental variables were consistent with our theoretical expectations, with the only exception of Internet IT Shock which turned out to have no effect on Knowledge Base Generality.

Robustness analyses

Alternative measures of Generality

Our measure of technological generality has been extensively used by prior research in both management and economics (e.g., Argyres and Silverman 2004, Chatterji and Fabrizio 2012, Moser and Nicholas 2004) and therefore it is our preferred choice. Nevertheless, two potential problems are inherent in this measure. First, being based on forward citations, it suffers from right truncation: more recent patents have a lower probability of receiving citations within the observation period. To ensure that our results are not biased by truncation we constructed an alternative measure of generality, labelled Normalized Generality. The measure is simply a normalized version of our original generality measure, where the normalizing factor is the number of forward cites received.

Second, reflecting the view that an organization's knowledge base is general insofar as it gets used across application sectors, our original measure of generality focuses on the forward citations received by that organization. As a robustness check, however, it may be useful to also measure the generality of organizations' technological knowledge in alternative ways that are not dependent on forward citations. To this end we constructed a second alternative measure of generality, called Classification Generality. Parallel to our original measure of generality, Classification Generality is calculated by taking all of a firm's patents in any given year and by computing (1 minus) a Herfindahl concentration index across USPTO primary classes. However, rather than the primary classes from which a firm's forward citations originate, this time the Herfindahl index pertains to the primary classes within which a firm's patents are classified by the USPTO patent examiner. This measure has been used in prior research to assess firms' technological diversity (e.g., Garcia-Vega 2006). Just like with our original generality measure, we take the logit transform of this variable to make it suitable to least squares regressions (again, zeros are transformed into 0.0001 and ones into 0.9999).

Figure 4 shows how the three measures of generality change over time. As it appears, both Normalized Generality and Classification Generality display a decline towards the end of the observation period, but this decline is less sharp than for our original measure. Table 3 report the results of these robustness checks. All models are fixed-effects 2SLS estimations with simultaneous effects, where the instrument set is the same as in the models reported in table 2. In models 7a and 7b, generality is measured by Normalized Generality, while in models 8a and 8b it is measured by Classification Generality. In all models, results are fully consistent with our main findings[6].

Missing values

All studies using Compustat data have many missing values. In the models reported in table 2, we dealt with missing values by imputing them through the *impute* command in Stata 12. Even though we used Compustat data exclusively to construct control variables, and not for our variables of theoretical interest, the share of missing values for the Compustat variables is substantial as it ranges from 28% to 38%. This casts a doubt on the validity of our control variables. To ensure that the results are not unduly influenced by our imputation of missing values, we ran two additional tests. First, we constructed a dummy variable (Dummy Missing) that identifies any observation associated with a missing value, and we added it as a control both in the first-stage and in the structural equations. As it turns out, Dummy Missing is positively associated with Knowledge Base Generality but not with Coreness (models 9a and 9b). More importantly, including this additional variable does not affect our effects of theoretical interest. Second, we took a more radical approach and excluded all cases associated with a missing value. As shown by models 10a and 10b, this more than halved the sample size but left unaltered our effects of interest.

Time and data truncation

The models reported in table 2 control for possible unit-invariant time-varying effects by means of sub-period (1985-1990, 1991-1996, 1997-2002) dummy variables. While this allowed us to capture the effects of time without a pre-specified functional form, often time is modelled by introducing a linear and a quadratic clock indicator. Models 11a and 11b report the results of models where time is specified in this way. Time has a curvilinear effect on both generality and coreness, although the hump is reversed. Modelling time in this way did not affect our effects of interest.

As mentioned, our measure of generality is right truncated as it is based on forward citations. While the two alternative measures of generality proposed above reassure us that our results are not unduly affected by right truncation, the problem of right truncation may affect more than just our

[6] Notice according the Sargan over-identification test, it cannot be concluded that the instruments are uncorrelated with the error of the structural equation in models 7b, 8a and 8b.

generality measure. Namely, inspecting the data shows a radical drop in the number of patents filed by the organizations in our sample after year 2000 that is at best suspicious. We suspect that this may reflect the fact that, even though Hall's updated NBER dataset supposedly covers up to 2004, some of the patents filed before 2006 had not yet been granted by the time the data were collected. It therefore seems safe to test whether our effects hold even if we restrict the observation period to the years prior to 2000. Models 12a and 12 b report the results of these tests: our effects of interest remain unaltered.

Conclusions

The key contention of this paper is that there exists a self-reinforcing, co-evolutionary relationship between an organization's knowledge base and network position. In particular, we argued that the more an organization moves towards the core of the R&D alliance network, the more it tends to build a generalist knowledge base with wide applicability across sectors. At the same time, the more an organization develops a generalist knowledge base, the more it tends to move towards the core of the R&D alliance network. We tested this co-evolutionary hypothesis using data on all R&D alliances registered in the US between 1985 and 2003, as well as patent-based and financial information on the organizations involved in those alliances. We found strong support for our hypotheses across a wide range of econometric specifications and robustness checks. By explicating how an organization's knowledge base co-evolves with the network of ties it maintains with other organizations, the present paper furthers our understanding of the nature and dynamics of organizations.

The paper contributes to the organizational debate in several ways. On a general level, we note that the theory developed in this study bridges two major intellectual divides that have traditionally generated alternative and seemingly incompatible views of the organization. The first divide originates from the fact that, even though organizational scholars typically assume the organization-environment link to be unidirectional, they radically diverge in what they postulate to be the locus and direction of causality. One tradition of organization theory argues that organizations are essentially forged, through either internal adaptation or environmental selection, by the environment with which they are faced (e.g., Volberda et al. 2012). As they assume environments to be "relatively intractable to manipulation by single organizations" (Astley and Van de Ven 1983, p. 249), advocates of this view theorize a one-way causal relation flowing from the environment to the organization, whereby an organization's conduct, resource profile, and performance are ultimately a reflection of the position it occupies within the broader environment. A second tradition of organizational research, conversely, emphasizes the role of the organization as an active agent that continuously navigates and transforms the environment in which it thrives (e.g., Song et al. 2002). According to this view, "the environment is not to be viewed as a set of intractable constraints" but, rather, as a relatively dynamic and malleable resource space that "can be changed and manipulated" and with which the organization interacts in an attempt to pursue its interests and opportunities (Astley and Van de Ven 1983, p. 249).

By demonstrating a co-evolutionary link between organizations and environment, the present study shows that although both theoretical perspectives are right in some important respects, neither is sufficient on its own to address the question it is after – how do organizations evolve? In line with the first tradition, we show that the position an organization occupies within the broader environment does influence the evolution of its internal resource profile. In line with the second view, however, we demonstrate that such influences run in the opposite direction too, as organizations systematically move across – and thereby transform – the external environment depending on the type of internal resources they develop. While we have no reason to expect that all aspects of an organization's internal resource profile will necessarily co-evolve with the external environment, exploring co-evolutionary dynamics such as the one unveiled in the presence study represents an opportunity to both gain deeper insight on the nature and evolution of organizations and to theoretically reconcile deep-seated but thus far unrelated streams of organizational scholarship.

The current paper also bridges a second intellectual rupture that has long characterized, and presumably hampered, the organizational debate. Some scholars, mostly drawing from structuralist sociology, argue that theories of organization should root causal claims in the structure of *opportunities* facing organizations. Others, mostly inspired by the so-called strategic choice view, argue that causal claims should be derived from an organization's *interests* (Astley and Van de Ven 1983). As Ahuja (2000a) and others (Sytch et al. 2012) have compellingly argued, however, neither opportunity-based nor interest-based arguments alone are sufficient to build satisfactory explanations of how organizations operate and how they relate to their external environment. In line with this argument, the present paper is premised on the explicit recognition that to understand the co-evolution of an organization's knowledge base and network position, it is essential to jointly consider both its opportunities and its interests structure. Following this explanatory logic, for example, we argued that whether an organization will move towards the core or towards the periphery of the R&D network depends on which alliances the organization is able to form (i.e., which R&D partners it attracts) *and* willing to form (i.e., which R&D partners it is attracted to).

In addition to establishing linkages across long-standing divides on the nature and evolution of organizations, the present study contributes to our understanding of organizations by advancing two prominent lines of theoretical development. Inter-organizational network theorists recognize the importance of core-periphery structures, arguing that the position an organization occupies within such structures deeply influences its behavior and performance (Cattani and Ferriani 2008, Connelly et al. 2011). While the effects of core-periphery structures have been examined in some depth, however, the question of why organizations come to occupy core or peripheral network positions has been left unattended. The present study proposes a novel answer to this question. We argued and showed that the more widely applicable is the technological knowledge developed by an organization, the greater are its incentives and opportunities to ally with organizations embedded within the core of the R&D network; consequently, the more the organization will tend towards the network core. Conversely, the more specialized an organization's technological knowledge becomes, the more the organization will drift towards the network periphery.

While the arguments developed in this paper are deeply rooted in received network theory, they change the way in which we think about network dynamics in one important way. Existing network explanations are largely premised on the view that todays' network position determines tomorrow's (Gulati and Gargiulo 1999), leaving moot why organizations *move* across network positions (Ahuja et al. 2012). Conversely, we drew insights from the knowledge-based view of the firm to argue that an organization's opportunity and interest structures – hence an organization's conduct – are not only a reflection of its current network position but also depend on the evolution of its internal knowledge base. While recently inter-organizational scholars have recognized the importance of incorporating organization-level theoretical mechanisms in network explanations (Operti and Carnabuci forthcoming), this line of theoretical development has yet to gain momentum. The present study contributes to this theoretical direction by articulating a set of causal mechanisms that explicitly relate an organization's knowledge base to its network dynamics. More generally, our results show that it is both possible and useful to integrate the rich body of theory on the knowledge-based view of the firm into existing network explanations.

This study also contributes new theory and evidence to the knowledge-based view of the firm. A key achievement of this literature has been to explain and show that a wide range of organizational outcomes, from the ability to combine previously unrelated technologies, to financial performance, are affected by an organization's knowledge base. What has been less explored in this literature, however, is the question of where does a firm's knowledge base come from and, more specifically, why do firms' knowledge bases develop in such different ways? The results of the present study offer novel insights into these questions. Drawing from network theory, we argued that an organization's network position affects both its opportunity structure (i.e., which knowledge it is exposed to and, hence, can potentially absorb) and its interest structure (i.e., which knowledge it is willing to develop). On these grounds, we hypothesized that an organization's position along the core-periphery structure of the R&D alliance network affects whether the firm will develop a generalist or a specialist knowledge base. Complementing the rich body of work on the effects of generalist and specialized knowledge on various organizational and strategic outcomes, our analyses extend the knowledge-based view of the firm by shedding light on the origins and evolution of firms' knowledge base.

Of course, this study is not without limitations. In line with our theoretical focus, and inspired by recent empirical evidence (Schilling 2009), we analyzed the evolution of a comprehensive R&D network comprising organizations from across *all* technological sectors. While this is a strength of this study, it brings with it two significant limitations. First, both the dynamics of R&D alliances and firms' patenting behavior may differ across R&D alliances, potentially leading to unobserved heterogeneity. While we tackled this issue by modeling organization-level fixed-effects in all our econometric specifications, this solution leaves open the possibility of unobserved heterogeneity across *pairings* of sectors. For example, do the alliance formation mechanisms postulated in this study apply equally when, say, a biotech firm allies with a pharmaceutical firm as when a chemical firm allies with an electronics firm? While we have no clear theoretical reason to answer negatively, empirically we are not able to address this question. Second, unlike industry studies, a limitation of our macroscopic approach is that it does not allow us to complement and triangulate our quantitative analyses with contextual, qualitative and historical information. While we are cognizant of these limitations, we are persuaded that the theory and evidence presented in this study deepen our understanding of the nature and dynamics of organizations and they lay the ground for further advancing organization theory.

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FIGURES AND TABLES

Figure 1. A core-periphery structure.

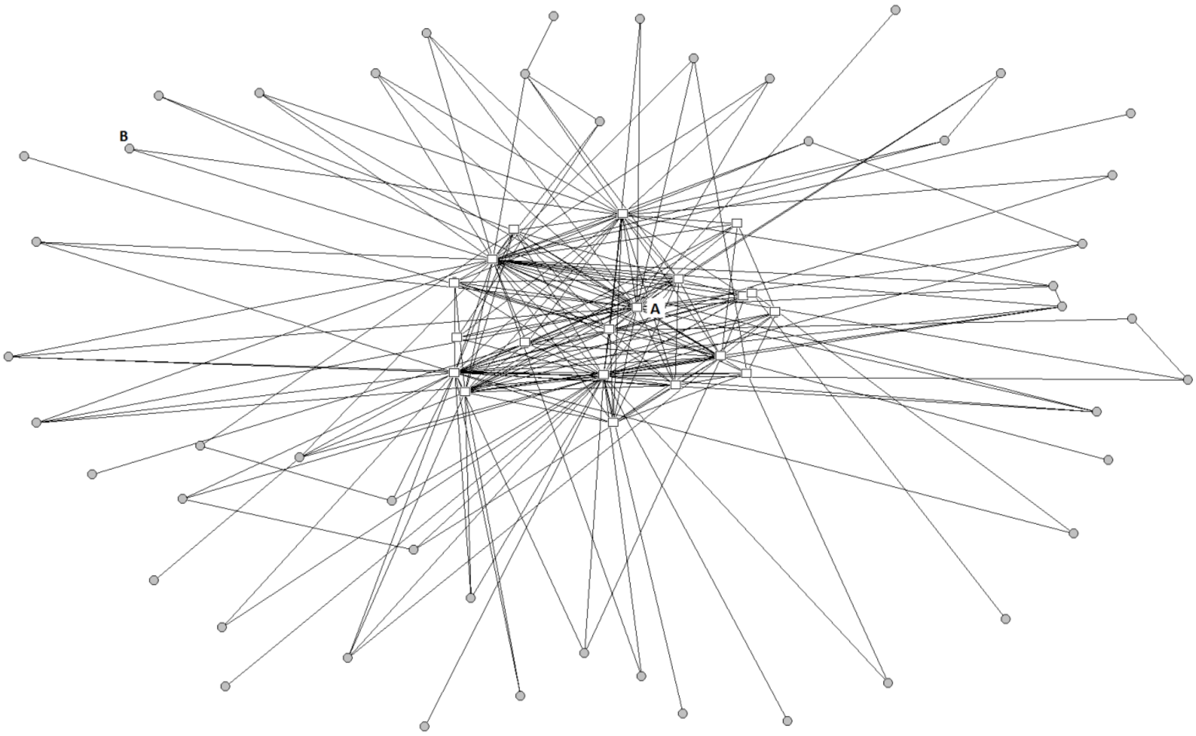

Figure 2. The evolution of the R&D alliance network

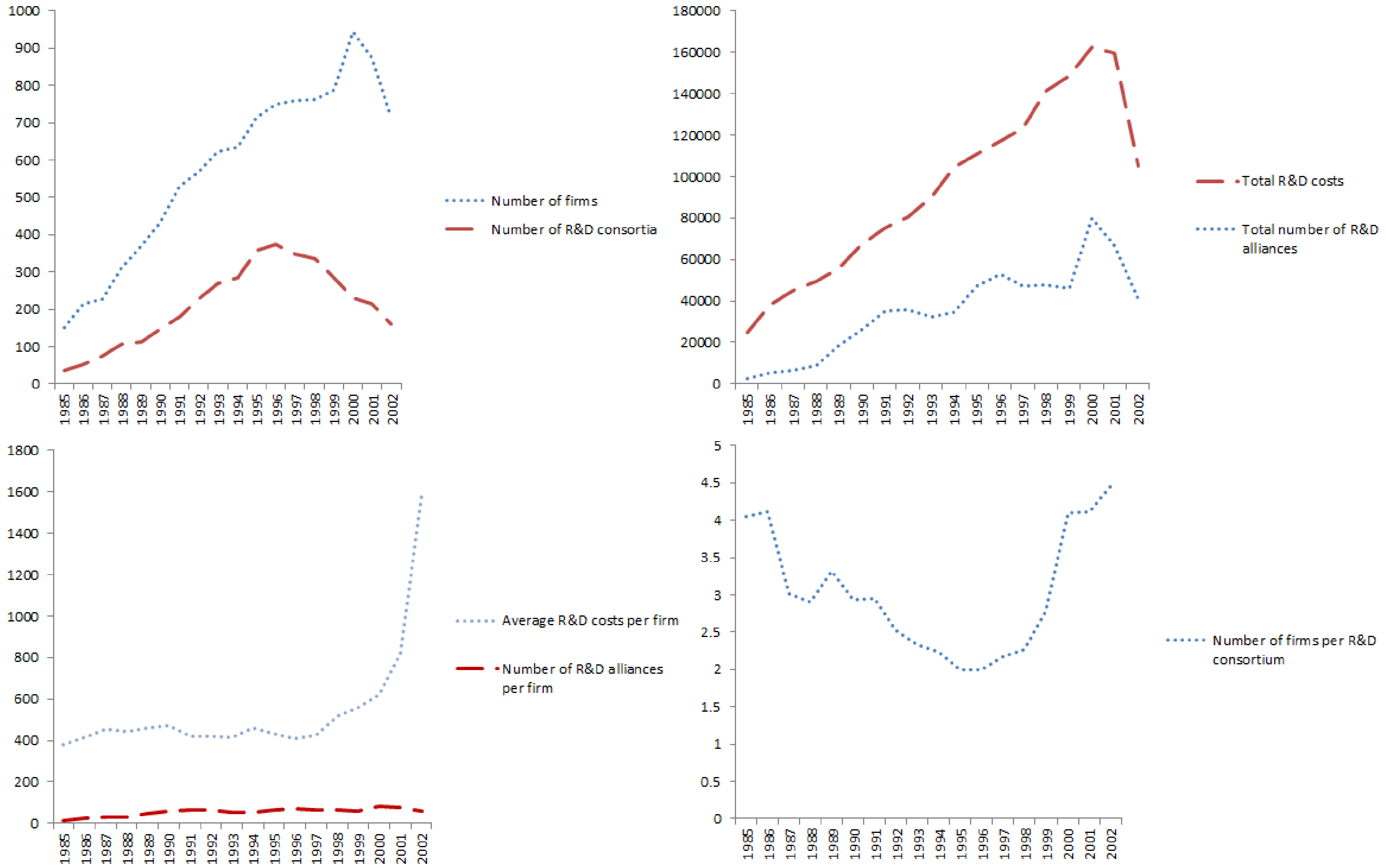

Figure 3. Fit with core-periphery model

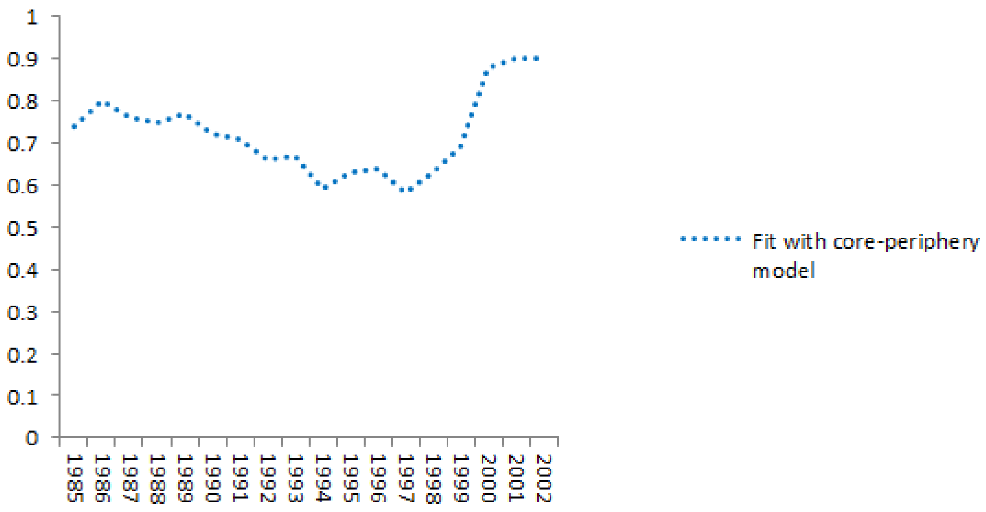

Figure 4. Average generality (3 alternative measures) over time

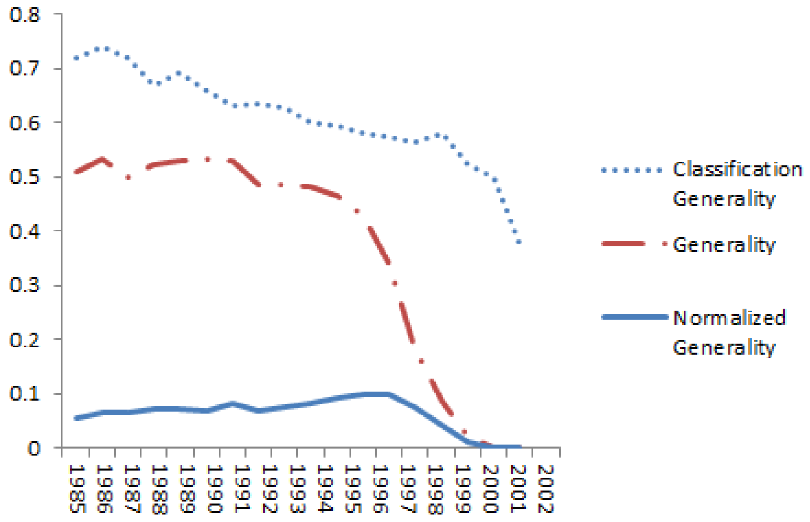

Table1. Means, standard deviations, and pairwise correlations

		Mean	S.D.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	Generality (logit transf.)	-2.84	5.01										
(2)	Coreness (logit transf.)	-5.62	3.43	0.09									
(3)	1985-1990 (dummy)	0.47	0.50	-0.52	0.00								
(4)	1991-1996 (dummy)	0.38	0.49	0.36	-0.01	-0.74							
(5)	EPS with extra items (ln)	0.74	0.82	0.21	0.05	-0.25	0.06						
(6)	Number of employees (ln)	2.07	2.03	0.11	0.17	-0.19	0.02	0.59					
(7)	R&D cost per employee	22.6	28.9	-0.21	-0.01	0.31	-0.16	-0.49	-0.47				
(8)	Effective size	32.6	48.0	0.01	0.50	0.14	-0.03	0.06	0.31	0.03			
(9)	IT 94-96 shock (dummy)	0.01	0.10	0.06	0.06	-0.09	0.13	0.03	0.01	-0.01	0.03		
(10)	California Earthquake	0.03	0.17	0.09	0.01	-0.17	0.23	-0.04	-0.12	0.06	0.00	-0.02	
(11)	State Property Net Subsidies	24.2	4.37	0.16	-0.05	-0.08	-0.05	0.08	0.06	-0.06	-0.04	-0.02	0.10

Table 2. OLS, 2SLS, and 3SLS regressions predicting Generality and Coreness with contemporaneous or lagged effects

	OLS, FE, no lag		OLS, FE, 1 yr lag		2SLS, FE, no lag		2SLS, FE, 1 yr lag		2SLS, FD, no lag		3SLS, FE, no lag	
	Model 1a	Model1b	Model 2a	Model 2b	Model 3a	Model 3b	Model 4a	Model 4b	Model 5a	Model 5b	Model 6a	Model 6b
	Generality (t)	Coreness (t)	Generality (t+1)	Coreness (t+1)	Generality (t)	Coreness (t)	Generalty (t+1)	Coreness (t+1)	Generality (Δt)	Coreness (Δt)	Generality (t)	Coreness (t)
Constant	1.733***	-6.011***	0.993**	-5.898***	34.605***	-6.657***	24.318***	-6.423***	0.760***	-2.090**	2.000	-1.523**
	(0.391)	(0.159)	(0.433)	(0.208)	(6.781)	(0.782)	(4.677)	(0.587)	(0.129)	(0.839)	(1.421)	(0.748)
Coreness	0.241***		0.229***		5.723***		4.190***		2.990***		1.732***	
	(0.0340)		(0.035)		(1.119)		(0.779)		(0.892)		(0.063)	
Generality		0.054***		0.035***		2.279***		1.273***		2.133***		0.522***
		(0.008)		(0.009)		(0.595)		(0.329)		(0.808)		(0.020)
EPS with extra items (ln)	0.985***	-0.074	0.634***	-0.103*	1.101***	-2.254***	0.612**	-1.342***	0.408***	-0.804**	1.016***	-0.533***
	(0.113)	(0.054)	(0.112)	(0.061)	(0.317)	(0.638)	(0.260)	(0.369)	(0.141)	(0.363)	(0.105)	(0.059)
Number of employees (ln)	-0.701***	0.231***	-0.210*	0.185***	-1.772***	1.686***	-1.182***	0.857***	-1.103***	1.986**	-0.993***	0.537***
	(0.105)	(0.050)	(0.108)	(0.059)	(0.365)	(0.457)	(0.316)	(0.241)	(0.218)	(0.788)	(0.098)	(0.054)
R&D cost per employee	-0.031***	0.005*	-0.033***	0.002	-0.048***	0.073***	-0.029**	0.064***	-0.006	0.002	-0.036***	0.019***
	(0.005)	(0.002)	(0.006)	(0.003)	(0.015)	(0.022)	(0.014)	(0.019)	(0.008)	(0.012)	(0.005)	(0.003)
1985-1990 (dummy)	-3.867***	-0.020	-2.004***	0.257**	-2.586***	8.705***	-0.983*	4.737***	0.852	-1.924*	-3.518***	1.815***
	(0.217)	(0.107)	(0.220)	(0.123)	(0.662)	(2.388)	(0.551)	(1.234)	(0.603)	(1.142)	(0.204)	(0.135)
1991-1996 (dummy)	0.076	0.084	0.273	0.387***	-0.415	-0.133	-0.311	0.0956	1.276**	-1.803*	-0.057	0.038
	(0.199)	(0.095)	(0.204)	(0.111)	(0.567)	(0.459)	(0.490)	(0.314)	(0.501)	(0.928)	(0.186)	(0.099)
Firm fixed effects	included	included	included	included	included	included	included	included	included	included	included	included
Observations	4,767	4,767	3,574	3,576	4,767	4,767	3,574	3,576	3,513	3,513	4,767	4,767
Number of firms	976	976	726	731	976	976	726	731	708	708	976	976
R-squared	0.247	0.022	0.159	0.016								
Sargan overid. test					0.536	0.715	0.140	0.210	0.238	0.208		
Endog. test					0.000	0.000	0.000	0.000	0.000	0.000		
Anderson underid. test					0.000	0.001	0.000	0.000	0.000	0.029		
Weak id. test (Wald F stat.)					13.816	7.305	15.965	8.194	9.657	3.548		

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are reported in parentheses. Reference category for period dummies is 1997-2002. In all models, both Generality and Coreness are logit transforms.
Coreness is instrumented in Models 2a, 3a, 4a, 5a, 6a. Generality is instrumented in Models 2b, 3b, 4b, 5b, 6b. In models 5a and 5b, all RHS and LHS variables are first-differenced.

Table 3. Alternative model specifications and robustness analyses

	Normalized generality		Classification generality		Dummy missing		Missings excluded		Time trend		Up to year 2000	
	Model 7a	Model 7b	Model 8a	Model 8b	Model 9a	Model 9b	Model 10a	Model 10b	Model 11a	Model 11b	Model 12a	Model 12b
	Normalized generality	Coreness	Classification generality	Coreness	Generality	Coreness	Generality	Coreness	Generality	Coreness	Generality	Coreness
Constant	18.556***	1.864	8.776***	-2.315**	34.321***	-7.036***	32.893***	-9.520***	14.341***	19.263***	29.784***	-5.437***
	(4.292)	(1.678)	(2.320)	(1.109)	(6.800)	(0.880)	(9.007)	(2.595)	(6.754)	(5.869)	(9.799)	(0.936)
Coreness	3.600***		1.701***		5.798***		5.922***		3.656***		4.968***	
	(0.710)		(0.383)		(1.153)		(1.661)		(0.883)		(1.615)	
Normalized generality		2.625***										
		(0.530)										
Classification generality				2.573***								
				(0.681)								
Generality						2.363***		3.163**		2.103***		2.810***
						(0.649)		(1.510)		(0.459)		(0.941)
EPS with extra items (ln)	0.692***	-1.640***	0.238**	-0.532**	1.042***	-2.367***	0.588	-2.605**	0.714***	-0.832***	0.892***	-1.396***
	(0.198)	(0.377)	(0.111)	(0.226)	(0.320)	(0.701)	(0.370)	(1.313)	(0.232)	(0.258)	(0.323)	(0.541)
Number of employees (ln)	-1.043***	1.126***	0.058	-0.860***	-1.774***	1.748***	-1.694**	3.340**	-1.118***	0.535***	-1.395***	1.197***
	(0.225)	(0.255)	(0.128)	(0.327)	(0.370)	(0.494)	(0.673)	(1.683)	(0.312)	(0.197)	(0.433)	(0.440)
R&D cost per employee	-0.026***	0.043***	-0.007	0.008	-0.050***	0.075***	-0.054**	0.105*	-0.019	-0.019*	-0.037**	0.044**
	(0.009)	(0.012)	-0.005	(0.008)	(0.015)	(0.023)	(0.027)	(0.057)	(0.013)	(0.011)	(0.017)	(0.021)
1985-1990 (dummy)	-0.520	3.309***	0.549**	-0.452	-2.557***	9.043***	-1.297	10.39**			-2.618***	8.866***
	(0.413)	(0.801)	(0.240)	(0.353)	(0.672)	(2.600)	(0.943)	(5.074)			(0.572)	(3.065)
1991-1996 (dummy)	0.0311	-0.842**	0.180	-0.711*	-0.424	-0.143	0.844	-0.252			-0.321	-0.0439
	(0.354)	(0.383)	(0.199)	(0.384)	(0.574)	(0.476)	(0.721)	(0.773)			(0.498)	(0.524)
Dummy missing					2.223**	1.083						
					(0.924)	(0.744)						
Time									1.248***	-4.545***		
									(0.277)	(1.061)		
Time (quadratic)									-0.050***	0.199***		
									(0.014)	(0.047)		
Firm fixed effects	included	included	included	included	included	included	included	included	included	included	included	included
Observations	4,609	4,609	4,723	4,723	4,558	4,558	2,151	2,518	4,558	4,558	4,215	4,215
Number of firms	774	774	799	799	767	767	375	434	767	767	736	736
Sargan overid. test	0.344	0.087	0.070	0.000	0.500	0.725	0.433	0.803	0.116	0.076	0.682	0.785
Endog. test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Anderson underid. test	0.000	0.000	0.000	0.001	0.000	0.001	0.001	0.114	0.000	0.000	0.006	0.011
Weak id. test (Wald F stat.)	13.614	12.555	14.976	7.611	13.352	6.607	6.917	2.166	10.309	11.125	5.193	4.473

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are reported in parentheses. Reference category for period dummies is 1997-2002. In all models, generality and coreness are instrumented.
All models are fixed-effects, 2SLS estimations with contemporanoues effects.